Management (Montevideo). 2025; 3:161
doi: 10.62486/agma2025161
ISSN: 3046-4048

ORIGINAL

A Cross-Cultural Leadership Behavior Prediction Model for Advancing Organizational and Global Management Practices

Un modelo de predicción del comportamiento de liderazgo intercultural para promover prácticas de gestión organizativa y global

Ashish Mohanty[1], Tanveer Ahmad Wani[2], Varalakshmi S[3], Zuleika Homavazir[4], Ankita Singh[5], Lavanya M[6]

[1]Department of Management, Institute of Business and Computer Studies, Siksha 'O' Anusandhan (Deemed to be University). Bhubaneswar, Odisha, India.
[2]Department of Physics, Noida International University. Greater Noida, Uttar Pradesh, India.
[3]Department of Management, Jain (Deemed to be University). Bangalore, Karnataka, India.
[4]ISME, ATLAS SkillTech University. Mumbai, India.
[5]Department of Commerce, ARKA JAIN University. Jamshedpur, Jharkhand, India.
[6]Master Of Business Administration, Sathyabama Institute of Science and Technology. Chennai, India.

Cite as: Mohanty A, Ahmad Wani T, S V, Homavazir Z, Singh A, M L. A Cross-Cultural Leadership Behavior Prediction Model for Advancing Organizational and Global Management Practices. Management (Montevideo). 2025; 3:161. https://doi.org/10.62486/agma2025161

Submitted: 27-02-2024 **Revised:** 27-06-2024 **Accepted:** 08-01-2025 **Published:** 09-01-2025

Editor: Ing. Misael Ron

Corresponding Author: Ashish Mohanty

ABSTRACT

In today's globally interconnected environment, recognizing culturally preferred leadership behaviors is dynamic for effective organizational and global management. This research presents a cross-cultural leadership behavior prediction model that employs advanced machine learning (ML) techniques to analyze and forecast leadership preferences across diverse cultural contexts. The research gathers data from Kaggle, comprising 6,945 responses across five countries, to analyze behavioral, demographic, and cultural aspects, and employs preprocessing techniques for improved model reliability. The model employs algorithms, such as the Scalable Golden Jackal Optimizer-driven Stacked Random Forest (SGO-SRF) to predict and uncover patterns in leadership behavior preferences. Cultural indicators and demographic features are analyzed using Recursive Feature Elimination (RFE) to identify their impact on these various leadership dimensions. The model was primarily applied using a baseline Random Forest (RF), then established through a Stacked RF approach, and finally optimized using the proposed hybrid SGO-SRF, which attained the highest performance across all evaluation metrics. The hybrid method was implemented in Python and it demonstrated superior performance, achieving higher accuracy (92,11 %), F1-scores (88,09 %), precision (81,98 %), and Recall (85,19 %). The research reveals that cultural values significantly influence leadership preferences, with long-term orientation affecting uncertainty tolerance, restraint affecting integration, and entrepreneurial values influencing structure, production emphasis, and predictive performance.

Keywords*:* Cross-Cultural Leadership; Leadership Behavior; Initiation of Structure; Scalable Golden Jackal Optimizer-Driven Stacked Random Forest (SGO-SRF).

RESUMEN

En el entorno globalmente interconectado de hoy en día, reconocer los comportamientos de liderazgo preferidos culturalmente es fundamental para una gestión organizativa y global eficaz. Esta investigación presenta un modelo de predicción del comportamiento de liderazgo intercultural que emplea técnicas avanzadas de aprendizaje automático (ML) para analizar y pronosticar las preferencias de liderazgo en diversos contextos culturales. La investigación recopila datos de Kaggle, que comprenden 6945 respuestas de cinco países, para analizar aspectos conductuales, demográficos y culturales, y emplea técnicas de preprocesamiento para mejorar la fiabilidad del modelo. El modelo emplea algoritmos, como el Stacked Random Forest (SGO-SRF) impulsado por el Scalable Golden Jackal Optimizer, para predecir y descubrir patrones en las preferencias de comportamiento de liderazgo. Los indicadores culturales y las características demográficas se analizan utilizando la eliminación recursiva de características (RFE) para identificar su impacto en estas diversas dimensiones del liderazgo. El modelo se aplicó principalmente utilizando un bosque aleatorio (RF) de referencia, luego se estableció mediante un enfoque de RF apilado y, finalmente, se optimizó utilizando el SGO-SRF híbrido propuesto, que alcanzó el mayor rendimiento en todas las métricas de evaluación. El método híbrido se implementó en Python y demostró un rendimiento superior, logrando una mayor precisión (92,11 %), puntuaciones F1 (88,09 %), precisión (81,98 %) y recuperación (85,19 %). La investigación revela que los valores culturales influyen significativamente en las preferencias de liderazgo, ya que la orientación a largo plazo afecta a la tolerancia a la incertidumbre, la moderación afecta a la integración y los valores emprendedores influyen en la estructura, el énfasis en la producción y el rendimiento predictivo.

Palabras clave: Liderazgo Intercultural; Comportamiento de Liderazgo; Iniciación de la Estructura; Bosque Aleatorio Apilado Impulsado por el Optimizador Golden Jackal Escalable (SGO-SRF).

INTRODUCTION

A leader plays a key role in organizations by controlling, training, and influencing groups and advances motivation through connection rather than submission. While traditional leadership focuses on control and competition, modern organizational demands are determined by change and digital transformation that require leadership capabilities. Conventional leadership views leadership as the sum of a leader's performance, often overlooking follower dynamics and evolving workplace contexts.(1) The domains of cross-cultural leadership and international management indicate that in order to effectively manage external affiliates and motivate employees in the nation of destination to achieve organizational objectives; international managers have to adapt their leadership behaviors.(2) Behavioral big data, which includes vast datasets on social and human behavior, has gained popularity in academia and business for user behavior prediction modeling. Internet companies forecast employer behavior for internal use and clients, using this information for targeting, customization, and decision-making. Significant predicted behaviors include purchases, churn, engagement, voting decisions, and life events for platforms and users.(3) Digital transformation has emerged as a key component of contemporary organizations' strategies. The capacity to lead teams through the complexity and unpredictability that come with digital transformation is essential to its success, and leadership is crucial in this situation.(4) Effective leadership is crucial for navigating digital transformation, as it guides the adoption of new technologies, fosters innovation, and manages organizational complexity.(5)

Research (6) explored the impact of cross-cultural factors on customer engagement (CE) and purchase intention in international settings. A conceptual model was developed and validated using data from 432 customers. Results show a strong link between cultural variables and CE, significantly affecting purchase decisions. However, the research is limited by regional coverage and might not capture global cultural diversity. The cross-cultural research (7) that involved 329 corporate employees found the connection between organizational excellence and servant leadership is mediated by employee competency. The research discovered that in a variety of cultural environments, servant leadership had a favorable effect on organizational outcomes. However, the cross-sectional methodology limits the findings and calls for more comprehensive, long-term research. Research (8) aims to understand cultural influences in employment interviews, focusing on impression management strategies. It connects cultural elements to differences in instant messaging habits, predicting cultural distance can lead to mismatches between applicant behavior and interviewer expectations, affecting interview performance evaluations. The model emphasizes the need for culturally sensitive hiring practices to minimize bias and improve global recruitment fairness. Research (9) explored the link between employee behavior and management strategies, highlighting their impact on workforce productivity and economic advancement. Artificial neural network (ANN) model to analyze communication, motivation, work satisfaction, and involvement. Results show that improved leadership, communication, and teamwork significantly enhance employee outcomes, with 70 % prediction accuracy. However, the model's generalizability might be limited due to project-specific parameters and contextual factors.

Objective

The research intends to develop a predictive model using ML to analyze the effect of cross-cultural and demographic factors on leadership behavior preferences for improving global and organizational management practices.

Rest of the paper

The research was organized into several sections. Section 1 explains the background and compares various kinds of literature relevant to the leadership behavior prediction model. Section 2 demonstrates the methodology. Section 3 depicts the results and discussion of the proposed approach. The research was concluded by section 4.

METHOD

An ML-based framework was proposed in the research for predicting leadership behavior preferences using cultural and demographic data. Data was sourced from a cross-cultural leadership dataset. Preprocessing was utilized to make the gathered data reliable. Feature selection was performed using RFE, and model optimization was achieved through the SGO. SRF architecture was employed to enhance prediction accuracy via layered ensemble learning. Figure 1 displays the individual flow of the methodology.

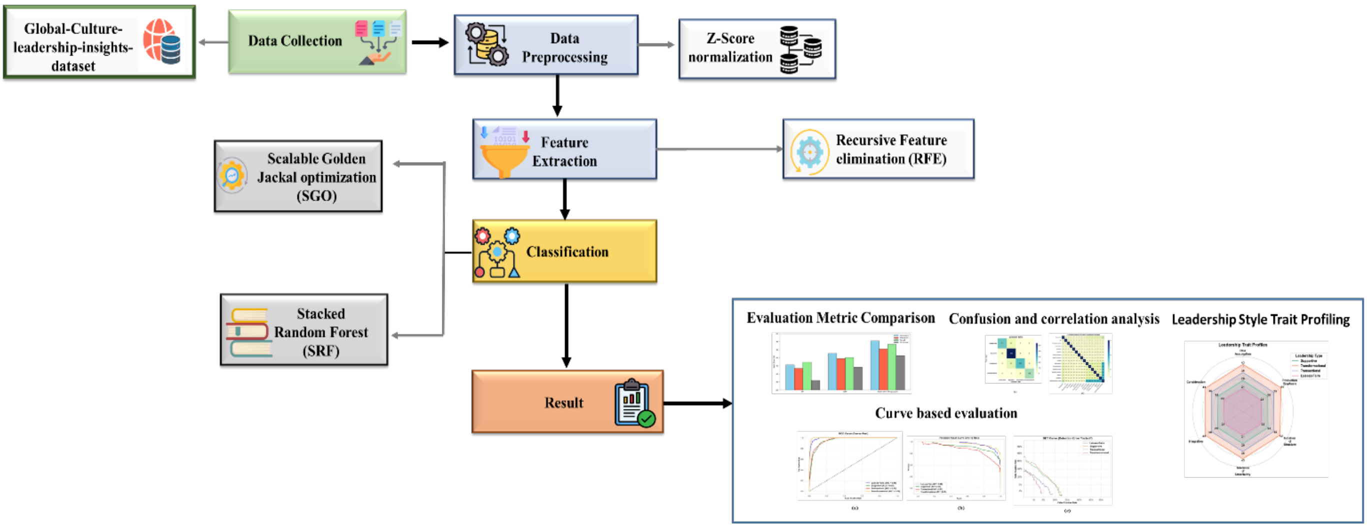


Figure 1. The process flow of the proposed technique

Data Collection

The cultural leadership data was gathered from the open-source called Kaggle: https://www.kaggle.com/datasets/zoya77/global-cultural-leadership-insights-dataset. The dataset examines cross-cultural leadership behavior in five countries. It includes responses from 6,945 people, examining how cultural and individual characteristics affect leadership standards. The dataset evaluates six main characteristics of leadership behavior. This information aids in designing culturally sensitive leadership strategies for multinational corporations, enhancing their effectiveness.

Data preprocessing using Z-score normalization

To ensure consistency in feature scale and eliminate the influence of unit differences across variables, Z-score normalization was applied to the numerical attributes. This step is crucial for improving the performance of algorithms like SGO-SRF to predict the leadership behavior by eliminating unit-based variance across input variables. This technique standardizes each feature by centering its values on the mean and scaling based on the standard deviation. The transformation is expressed in equation (1).

$$Z = \frac{y-\mu}{\sigma} \qquad (1)$$

Where is the original value, μ represents the mean of the feature and the standard deviation is represented as σ. This normalization makes all features and assists in overcoming the convergence as well as bias in training. It computes particularly well when being applied to the implemented SGO-SRF method, which is sensitive to magnitudes of features that can easily recognize the cross-cultural behavior, with ensemble models and optimization-driven frameworks adopted in the research.

Feature Extraction based on Recursive Feature Elimination (RFE)

The process of identifying and selecting relevant variables from raw data that contribute meaningfully to model predictions is termed feature extraction. RFE is applied in the research to remove methodically several input features and retain only those most significant in predicting leadership behavior preferences. In this research, RF is used as the base learner within RFE due to its robustness in handling complex, high-dimensional datasets and its ability to rank feature importance. Equation (2) provides the importance of a given node within a decision tree.

$$m_{ji} = x_i D_i - x_{left(i)} D_{left(i)} - x_{right(i)} D_{right(i)} \qquad (2)$$

Where m_{ji} is the importance score of nodes i; x_i denotes the weighted number of samples reaching node i; D_i represents the impurity of node i; and left(i), right(i) are the left and right child nodes, respectively. This formulation helps quantify how much each feature contributes to reducing impurity, thereby guiding the recursive elimination process. By selecting features with the highest cumulative importance, RFE enhances the model's ability to generalize across culturally diverse leadership data.

Scalable Golden Jackal Optimizer-driven Stacked Random Forest (SGO-SRF)

The SGO method, a combination of meta-heuristic optimization and ensemble method, is used to drive SRF, enhancing accuracy and decision-making. Its adaptive search dynamics help to find the best feature weighting and model setting, making it suitable for complex prediction activities like modeling cross-cultural leadership behavior. The stacked structure integrates several RF for amplified decision robustness.

Stacked Random Forest (SRF)

An ensemble-based approach, RF incorporates various decision trees trained on different subsets of data and features to develop prediction robustness. While single trees might overfit in complex or imbalanced datasets, RF reduces variance and enhances generalization through randomized training. In this research, an SRF model is used, where outputs from each RF layer serve as inputs to the next. This stacking mechanism permits the system to improve earlier predictions by capturing hidden patterns and addressing uncertainty, thereby enhancing the accuracy of leadership behavior classification.

Leadership Behavior Prediction Using Ensemble Learning

The research intends to predict leadership behavior preferences relying on cross-cultural and demographic data. A large ensemble model (SRF) is used to manage high-dimensionality, decrease overfitting, and enhance the reliability of predictions. The model is constructed sequentially with layers of RF classifiers with the output of one as the input to another one. Equation (3) represents that a prediction made by a single SRF at a level is averaged over all the trees in a particular layer.

$$p_k(y) = \frac{1}{S} \sum_{s=1}^{S} \quad p_s^{(k)}(y) \qquad (3)$$

This equation computes the probability that the input sample y belongs to class y, based on the ensemble output of S trees at level k.

Stacking and Feature Enhancement Across Layers

Stacked learning allows the model to carry forward not only the original input data but also the predicted class probabilities from previous layers. This enables the next level to learn from the prediction confidence of earlier layers, thereby improving semantic understanding and reducing misclassification in closely related leadership traits. At each subsequent level, the feature vector is augmented that was represented in equation 4.

$$w^{(k)} = [w, p_{k-1}(y)] \qquad (4)$$

Here, the new input w^k includes both the original features and the class probability vector from the previous level. The model uses SRF architecture to distinguish subtle behavioral differences across cultures. It passes through all k stacking levels and selects the class with the highest posterior probability, resulting in the leadership behavior class with the highest probability. This approach leverages diversity of RF and depth of stacked generalization for accurate, culturally sensitive predictions, making it ideal for modeling nuanced leadership behavior patterns in cross-cultural contexts.

Scalable Golden Jackal Optimization for Leadership Behaviour Prediction

The Golden Jackal Optimization (GJO) algorithm, inspired by golden jackal cooperative hunting, consists of stages of prey probing, encircling, and attacking. However, the initial version is unstable due to random jackal positions, causing suboptimal exploration and decreased predictive performance. The SGO dynamically scales step sizes during early search. This enhances feature selection and model parameter adjustment for culturally diverse data sets. The updated position of jackals in the SGO is calculated using equation (5).

$$W(s+1)_{Modified} = ScaSF\left(\frac{W_1(s)+W_2(s)}{2}\right) \qquad (5)$$

Where the Sine Cosine Adaptive Scaling Factor (ScaSF) is defined in equation (6).

$$ScaSF = \{sin\ \sin\left(X_{s1} - X_{s2} * \left(\frac{s}{S\ max}\right)\right)$$
$$if\ RD < 0.5\ \ cos\ \cos\left(X_{s1} - X_{s2} * \left(\frac{s}{S\ max}\right)\right) \qquad (6)$$
$$if\ RD \geq 0.5$$

Here, RD is a random number in [0, 1]. s is the current iteration. S max is the maximum number of iterations and X_{s1} and X_{s2} are weighting factors chosen based on empirical testing through experimentation, the best convergence performance was achieved. The proposed SGO-SRF hybrid model improves leadership behavior prediction accuracy across different cultural and demographic groups by combining adaptive optimization potentials of SGO and strong ensemble power of SRF. This enhances feature selection and forecasting accuracy in culturally diverse datasets, proving at generalization and reliability of cross-cultural leadership behavior prediction.

RESULTS AND DISCUSSION

This section presents the experimental outcomes of the proposed leadership behavior prediction model and evaluates its effectiveness using python through comparative analysis. The performance of three models, RF, SRF, and the proposed SGO-SRF is assessed using key classification metrics. The results intend to validate the improvement achieved through recursive feature selection, meta-heuristic optimization, and ensemble stacking techniques.[10,11]

Model Evaluation and Feature Correlation Analysis

The model for predicting leadership behavior was tested using a confusion matrix, which classified leadership styles into four categories: Laissez-Faire, Supportive, Transactional, and Transformational. Additionally, a heat map was created based on the correlation between cultural dimensions, demographic characteristics, and leadership behavior variables from the cultural behavior prediction dataset.[12,13]

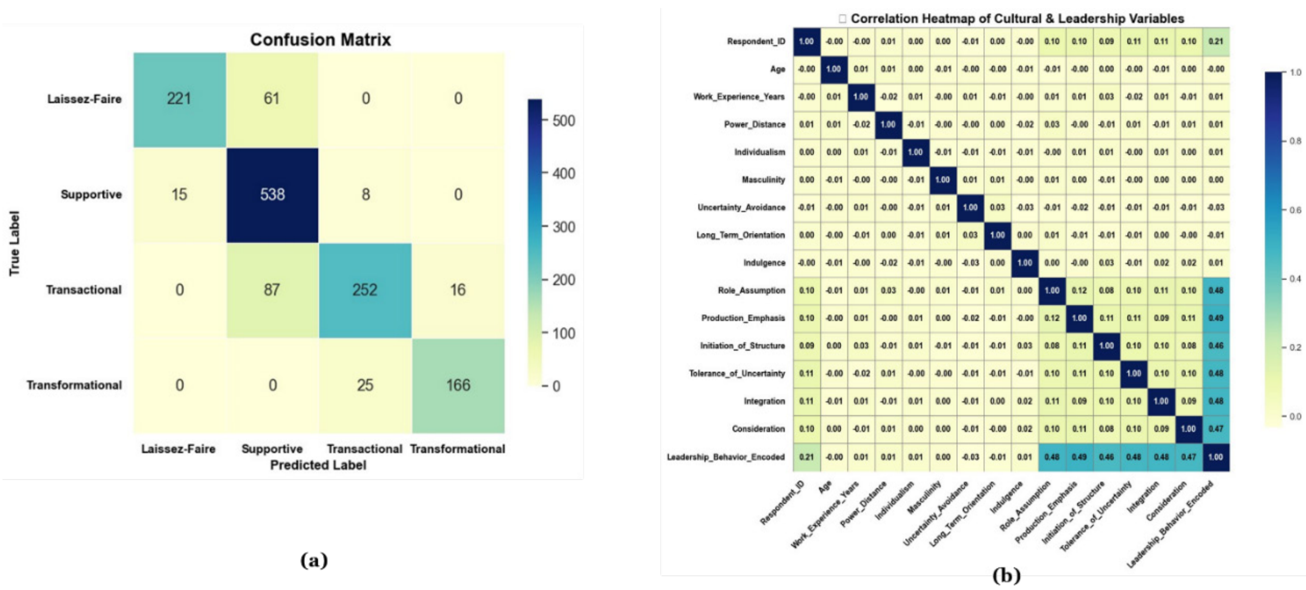
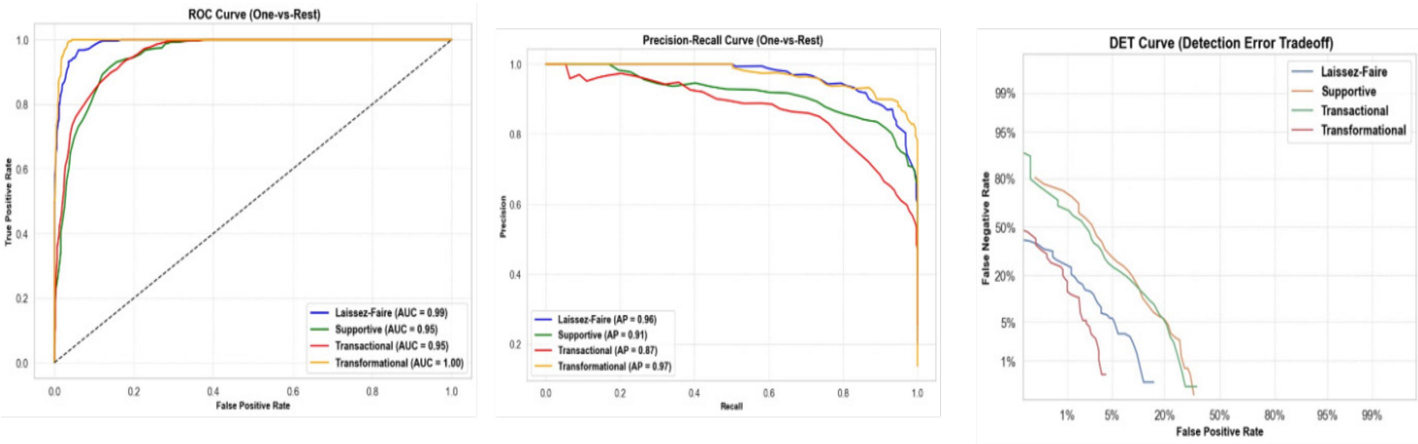


Figure 2. Graphical Representation of (a) Confusion Matrix, (b) Correlation Matrix

The model accurately identified Supportive and Transformational leadership, as shown in figure 2(a). The correlation heatmap in figure 2(b) shows strong positive correlations between cultural dimensions like Long-Term Orientation, Power Distance, and leadership behaviors like Initiation of Structure and Production Emphasis, highlighting the interconnection between input features.(14,15)

Discriminative Power Analysis Using ROC, Precision-Recall, and DET Curves

To further prove the adequacy of the proposed SGO-SRF model, several evaluation curves were used: Receiver Operating Characteristic (ROC), Precision-Recall (PR), and Detection Error Tradeoff (DET). These measures give a clear view of the overall modeling power of the model on all four classes of leadership behaviors.(16,17)



(a) (b) (c)

Figure 3. Graphical Representation of (a) ROC Curve (b) Precision-Recall Curve (c) DET Curve across all classes

Figure 3 presents the ROC, PR, and DET curves obtained using a One-vs-Rest classification strategy. The model's ROC curves show high AUC values for all classes, indicating excellent discriminatory capability. The Precision-Recall curve confirms robustness, especially in handling imbalanced distributions. Transformational leadership shows the strongest separation from other classes. The DET curve reveals a trade-off between false positive and false negative rates.(18,19)

Leadership Style Trait Profiling

Based on the six key characteristics, differences between leadership styles are examined across specific behavioral dimensions. Such visualization helps in profile each leadership style in terms of behavioral inclinations and preferred actions. Figure 4 shows a radical-based representation of the trait profiling.(20,21)

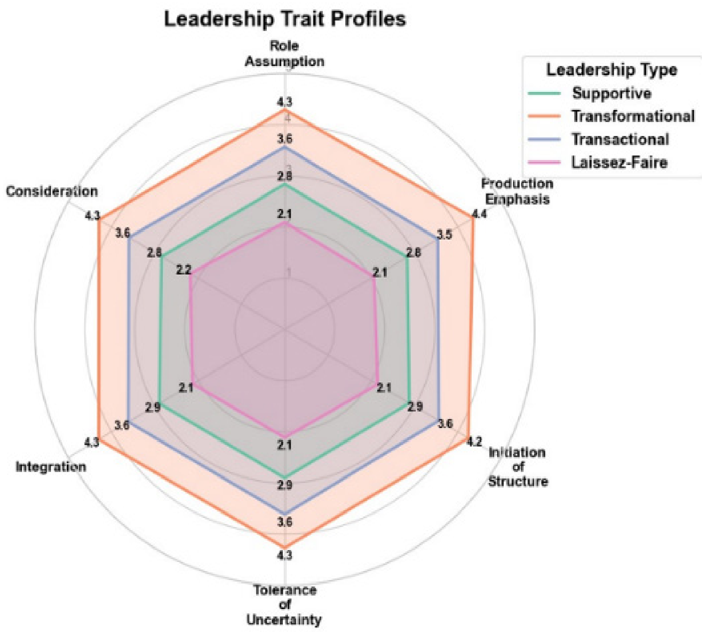


Figure 4. Illustration of average scores for six key leadership traits

Figure 4 shows four leadership traits: Supportive, Transformational, Transactional, and Laissez-Faire. Transformational leadership is highest in Consideration, Integration, Tolerance of Uncertainty, and Role Assumption, demonstrating strong interpersonal and strategic abilities. Supportive leadership is high in Consideration, Integration, and Tolerance of Uncertainty but slightly low in Transformational. Transactional leadership is moderate and less flexible. Laissez-Faire leadership can help in leadership training and culture flexibility training.(22,23)

Evaluation Metrics

A comparison of the proposed SGO-SRF model in predicting leadership behavior was compared between RF and SRF models to determine their effectiveness. Research is conducted regarding four important classification parameters, namely Accuracy, Precision, Recall, and F1-Score. The metrics give an overarching sense of model performance as regards the correctness and reliability of classification. Table 1 and figure 5 illustrate the results received to conclude the enhanced performance.(24)

Table 1. Performance comparison of metrics over methods

Metrics	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RF	92,15	91,69	92,48	90,21
SRF	93,56	92,89	93,02	91,83
SGO-SRF (Proposed)	95,11	94,08	94,67	93,26

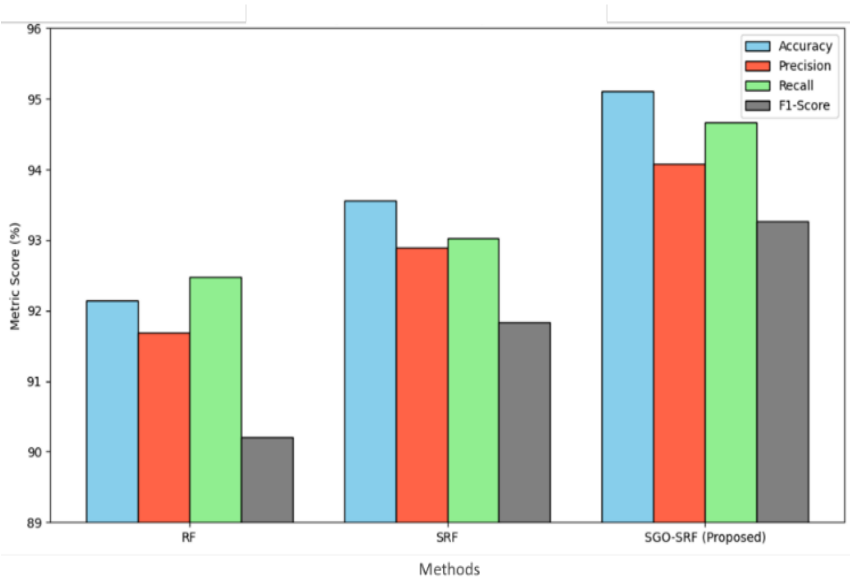


Figure 5. Graphical Representation of metrics evaluation performance

The findings indicate that the suggested SGO-SRF model is superior compared to both RF and SRF in all measures. It attains the best results in accuracy (95,11 %), precision (94,08 %), recall (94,67 %), and F1-score (93,26 %), meaning better generalization and class discrimination performance. The addition of ScaSF to the GJO procedure improves predictive stability on culturally diverse output datasets, enhancing its usefulness in leadership data. The proposed SGO-SRF model addresses limitations in RF and SRF approaches, such as limited feature handling, poor generalization, and insufficient sensitivity to cultural variability. It uses recursive feature elimination and meta-heuristic optimization to select impactful features, enhancing prediction stability and accuracy, and capturing complex relationships in cross-cultural datasets.(25)

CONCLUSIONS

Despite growing global integration, predicting culturally aligned leadership behavior remains challenging due to the complexity and variability of demographic and cultural factors. This research intends to develop a robust prediction framework that captures cross-cultural leadership preferences using ML. Specifically, the objective is to improve prediction accuracy and feature relevance by integrating optimization and ensemble learning techniques. Effective cross-cultural leadership modeling is vital for global management and organizational success. This research achieved significant improvements using the proposed SGO-SRF model, with accuracy reaching 95,11 %, precision at 94,08 %, recall at 94,67 %, and F1-score 93,26 %. However, the research is limited

https://doi.org/10.62486/agma2025161 ISSN: 3046-4048

to static, questionnaire-based data from five cultural regions, which cannot fully capture dynamic behavioral shifts. Future research should combine real-time data streams, expand cultural diversity, and explore hybrid learning frameworks to further enhance generalization and applicability in global HR and leadership analytics.

BIBLIOGRAPHIC REFERENCES

1. Sagbas M, Oktaysoy O, Topcuoglu E, Kaygin E, Erdogan FA. The mediating role of innovative behavior on the effect of digital leadership on intrapreneurship intention and job performance. Behavioral sciences. 2023 Oct 23;13(10):874.

2. Tsai CJ. Cross-cultural leadership behavior adjustment and leader effectiveness: A framework and implications. International Studies of Management & Organization. 2022; 52(3-4):205-225. https://doi.org/10.1080/00208825.2022.2131232

3. Edet Usoro I, Akhigbe RO, Promise Ogolodom M, Shuaibu A, Emeka Ezugwu E, Titi Oyegbata O, et al. Biointerfaces in sensors and medical devices: challenges, materials, and solutions for biological integration. eVitroKhem. 2025; 4:256.

4. Alejandro Gerlero M. Gamified web application with artificial intelligence for teaching programming in Spanish-speaking contexts. EthAIca. 2025; 2:55.

5. Estrada Meza RU, González Pérez MG. Analysis of public transport fares in Guadalajara, Mexico. Transport, Mobility & Society. 2023; 2:72.

6. Rodríguez-Portelles AC, Céspedes Rómulo AM. Infrared Thermography as a Diagnostic Tool in Podiatry: Advances, Applications, and Perspectives. Podiatry (Buenos Aires). 2025; 4:156.

7. Shmueli G, Tafti A. How to "improve" prediction using behavior modification. International Journal of Forecasting. 2023; 39(2):541-555. https://doi.org/10.1016/j.ijforecast.2022.07.008

8. Sacavém A, de Bem Machado A, dos Santos JR, Palma-Moreira A, Belchior-Rocha H, Au-Yong-Oliveira M. Leading in the Digital Age: The role of leadership in organizational digital transformation. Administrative Sciences. 2025; 15(2):43. https://doi.org/10.3390/admsci15020043

9. de Paúl AN, Farina P, Aranguren A, Portis A. Violence: manifestations in the health field. South Health and Policy. 2025; 4:230.

10. Nasser S, González H. Environmental Planning Strategies for the Sustainability of the Agricultural Sector. Environmental Research and Ecotoxicity. 2024; 3:114.

11. Aitken Gutierrez JH, Gamonal Torres CE, Ordoñez Mejia CA, Fernández Gastelo SX. Improving thermal comfort in educational environments: an innovative approach. Land and Architecture. 2024; 3:103.

12. Rocha C, Leitão L, Gonçalves A, Rodrigues C, Bento A filipa, Severino S, et al. Compassion fatigue, quality of care and clinical governance. Nursing Depths Series. 2025; 4:406.

13. Porfírio JA, Carrilho T, Felício JA, Jardim J. Leadership characteristics and digital transformation. Journal of Business Research. 2021; 124:610-619. https://doi.org/10.1016/j.jbusres.2020.10.058

14. Chatterjee S, Chaudhuri R, Vrontis D. Examining the role of cross-cultural factors in the international market on customer engagement and purchase intention. Journal of International Management. 2022; 28(3):100966. https://doi.org/10.1016/j.intman.2022.100966

15. Miló Valdés CA, Pérez Acevedo LC, Vitón Castillo AA. Utility of immunoinformatics in epitope mapping for vaccine and therapeutic design. eVitroKhem. 2025; 4:152.

16. Matos Matos A. Algorithmic biases in mental health diagnoses and their impact on vulnerable populations: a documentary review of advances and challenges. EthAIca. 2022; 1:20.

17. Piñerez Díaz FJ, Sorrentino E, Caldera Molleja OA. Quality management system for Cardón Rent Car, C.A. Transport, Mobility & Society. 2025; 4:159.

18. Malagón Silva B. Trends in the use of artificial intelligence in the treatment of diabetic foot. Podiatry (Buenos Aires). 2025; 4:152.

19. Irfan M, Salameh AA, Saleem H, Naveed RT, Dalain AF, Shahid RM. Impact of servant leadership on organization excellence through employees' competence: Exploring a cross-cultural perspective. Frontiers in Environmental Science. 2022; 10:985436. https://doi.org/10.3389/fenvs.2022.985436

20. Arseneault R, Roulin N. A theoretical model of cross-cultural impression management in employment interviews. International Journal of Selection and Assessment. 2021; 29(3-4):352-366. https://doi.org/10.1111/ijsa.12348

21. Choque Ccanchi CA, Quintana Dragichevich CO, Meneses Claudio BA, Zapana Ruiz JA. Occupational Health and Safety Management: Impact on Work Performance and Risk Prevention. South Health and Policy. 2023; 2:62.

22. Mandelman T, Navas C. Strategies for sustainable growth in competitive environments. Environmental Research and Ecotoxicity. 2022; 1:20.

23. Almirón Cuentas JA, Bernedo-Moreira DH. Multisensory Design in Education: How Architecture Enhances the Learning Experience. Land and Architecture. 2024; 3:104.

24. Dias D, Reis J, Nunes N, Ruxa S, Severino S, Sousa L. Nurse leadership and the challenges of clinical governance in emergency settings: a theoretical and reflective analysis. Nursing Depths Series. 2025; 4:407.

25. Lee C. Artificial Neural Networks (ANNs) and Machine Learning (ML) modeling employee behavior with management towards the economic advancement of workers. Sustainability. 2024; 16(21):9516. https://doi.org/10.3390/su16219516

FINANCING
None.

CONFLICT OF INTEREST
Authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION
Conceptualization: Ashish Mohanty, Tanveer Ahmad Wani, Varalakshmi S, Zuleika Homavazir, Ankita Singh, Lavanya M.
Data curation: Ashish Mohanty, Tanveer Ahmad Wani, Varalakshmi S, Zuleika Homavazir, Ankita Singh, Lavanya M.
Formal analysis: Ashish Mohanty, Tanveer Ahmad Wani, Varalakshmi S, Zuleika Homavazir, Ankita Singh, Lavanya M.
Drafting - original draft: Ashish Mohanty, Tanveer Ahmad Wani, Varalakshmi S, Zuleika Homavazir, Ankita Singh, Lavanya M.
Writing - proofreading and editing: Ashish Mohanty, Tanveer Ahmad Wani, Varalakshmi S, Zuleika Homavazir, Ankita Singh, Lavanya M.